Understanding and assessing climate-driven mortality risk

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Outline of the presentation

1. Background information
2. Joint extremes in temperature and mortality
3. Excess mortality under climate scenarios
4. Cold-related cause-of-death mortality
5. The ultimate research questions

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The link between climate change and human mortality

- Approximately **9** out of every **100** deaths in the world during 2000–2019 were due to extreme cold temperatures. - A recent study
- During 2000–2019 , the mortality burden attributable to extreme temperatures in Australia is estimated to be **11.40%** of the total deaths. - A recent study
- Between 2030 and 2050, climate change is expected to cause approximately **250,000** additional deaths per year. - WHO

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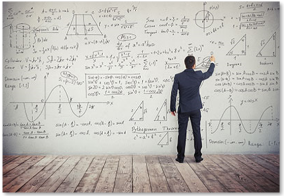
What can insurance do in a changing climate?

Unanticipated adverse claim experience due to climate change can lead to insolvency of insurance and reinsurance companies.



Enterprise Risk Management

Identify → **Understand** → **Quantify** → **Mitigate**

How can climate change kill you?

According to the WHO:

Between **2030** and **2050**, climate change is expected to cause approximately **250,000** additional deaths **per year**.

Weather-related catastrophes (etc. floods, bushfires and earthquakes)

Extreme temperatures (etc. heat waves and cold spells)

Climate-sensitive infectious diseases (etc. malaria disease and vector-borne diseases)

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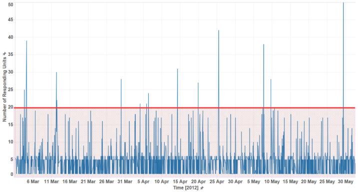
The key challenge

A key challenge in modeling extreme risks: scarcity of extreme events. Extreme value theory (EVT) tackles this problem by providing results beyond observed values.

- **Block Maxima**:
  Distribution of the sample maximum
- **Peaks Over Threshold**:
  Distribution of values over a high threshold



A simplified example:

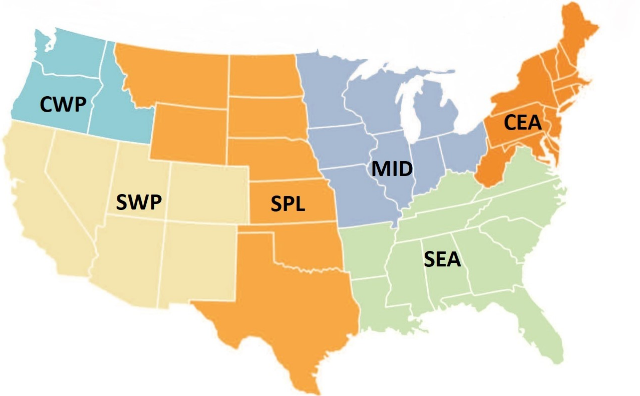
Univariate POT:

The temperature is $> 43°$, how likely is it to be $> 45°$?

Bivariate POT:

The temperature is $> 43°$, how likely is it that > 20 people die?

Data Description and Modeling



Source: Actuaries Climate Index Executive Summary (2018), Page 4, Figure 2

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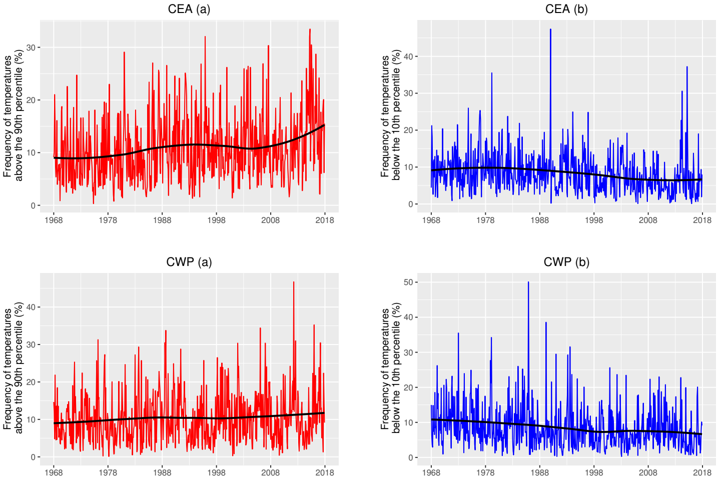

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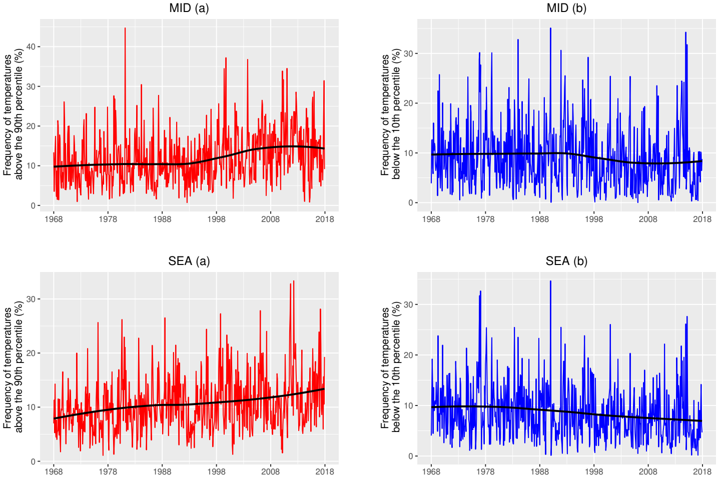

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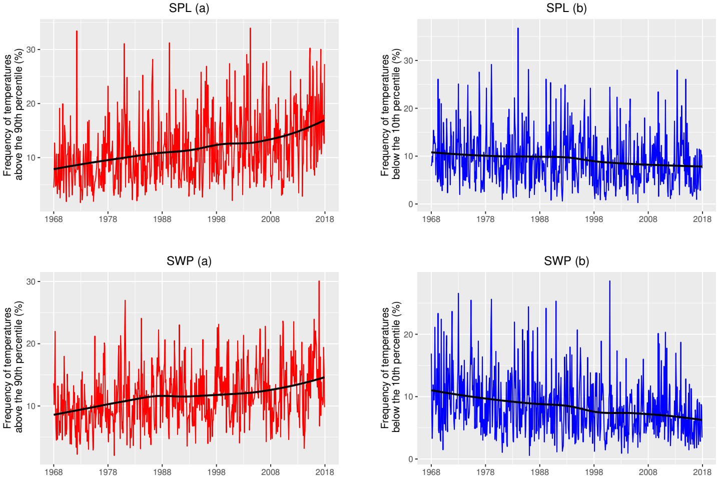

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Data Description and Modeling

We adopt the seasonal ARIMA model which incorporates both non-seasonal and seasonal factors in a multiplicative model, which can be expressed as

$$\text{ARIMA}(p,d,q) \times (P,D,Q)_S, \tag{1}$$

where:

- p, d, and q denote the order of the AR model, the order of differencing, and the order of the MA model in the non-seasonal part, respectively,
- P, D, and Q denote the order of the AR model, the order of differencing, and the order of the MA model in the seasonal part, respectively, and
- S is the time span of repeating the seasonal pattern. Since we are modeling monthly $T90$ and $T10$ time series, S is set to be 12.

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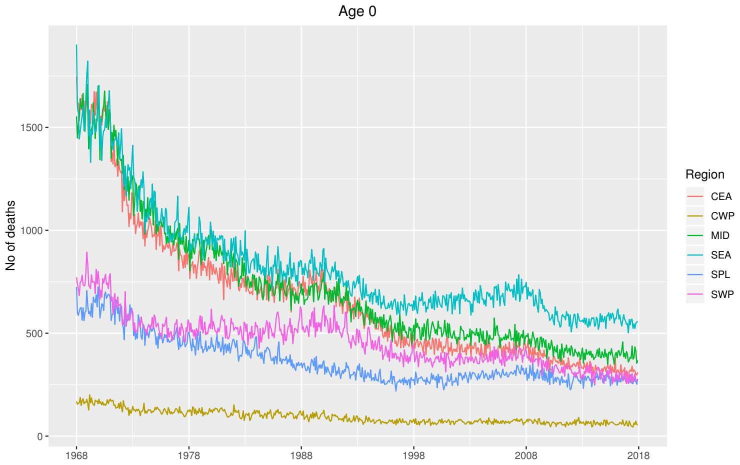
Data Description and Modeling



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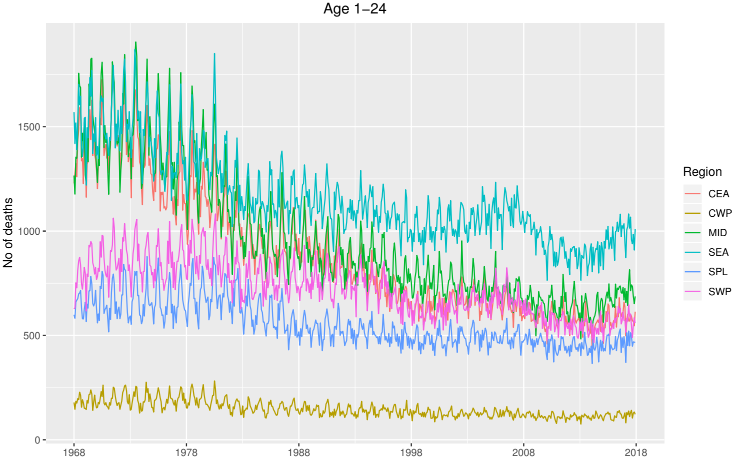

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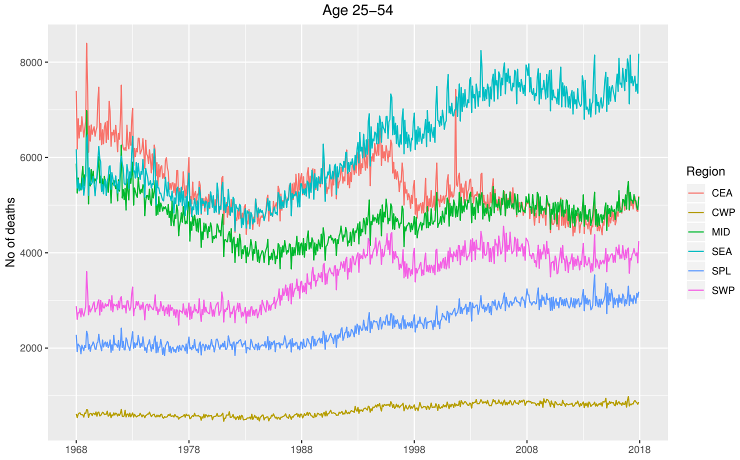

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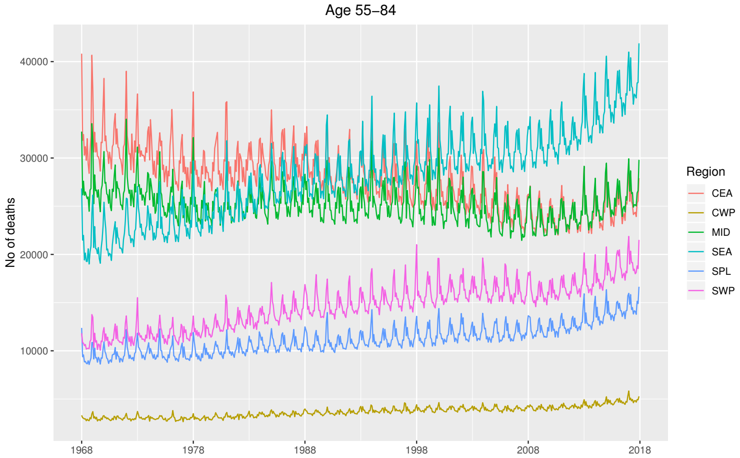

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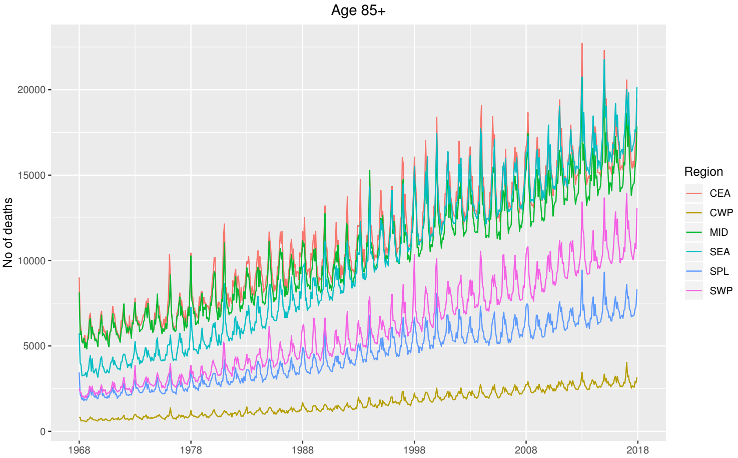

Data Description and Modeling

Similar to $T10$ and $T90$, we want to obtain the "noise" in death counts via time series models.

- We fit a seasonal ARIMA model first.
- We include the GARCH component if the resulting residuals fail the Ljung-Box test at 5% level of significance.
- The optimal model is selected based on AIC.

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Multivariate Extreme Value Theory

Consider a random variable X with distribution F on $\mathbb{R}$ and denote by M_n the maximum of a sample of size n from F. If there exist norming constants $a_n > 0$ and $b_n \in \mathbb{R}$ such that

$$\lim_{n\to\infty} \Pr\left(\frac{M_n - b_n}{a_n} \leq y\right) = G(y), \qquad y \in \mathbb{R}, \tag{2}$$

then we say that F belongs to the max-domain of attraction of G, and call G a generalized extreme value (GEV) distribution. The GEV distribution function G must be of the same type as

$$G(y) = \exp\left\{-\left(1+\gamma\frac{y-\mu}{\sigma}\right)_+^{-1/\gamma}\right\}, \tag{3}$$

where $\mu \in \mathbb{R}$, $\sigma > 0$, and $\gamma \in \mathbb{R}$ are the location, scale, and shape parameters, respectively, and $c_+ = \max(c, 0)$.

Multivariate Extreme Value Theory

Following the works of Balkema and de Haan (1974) and Pickands (1975), the conditional distribution of the normalized exceedance over a high threshold converges to a generalized Pareto distribution (GPD), that is,

$$\lim_{n\to\infty} \Pr\left(\frac{X-b_n}{a_n} \le y \,\middle|\, X > b_n\right) = H(y), \qquad y > 0, \tag{4}$$

where H is of the same type as

$$H(y) = 1 - \left(1 + \gamma\frac{y-\mu}{\sigma}\right)_+^{-1/\gamma}, \tag{5}$$

with the location, scale, and shape parameters $\mu \in \mathbb{R}$, $\sigma > 0$, and $\gamma \in \mathbb{R}$. The GPD H above is supported on the region of y defined by $y > 0$ and $1 + \gamma\frac{y-\mu}{\sigma} > 0$.

Multivariate Extreme Value Theory

Consider a d-dimensional random vector $\boldsymbol{X}$ with distribution F on $\mathbb{R}^d$ and denote by $\boldsymbol{M}_n$ the component-wise maximum of a sample of size n from F. The limit distribution G, called a multivariate GEV distribution, has marginal distributions G_i for $1 \leq i \leq d$ identical to

$$\lim_{n\to\infty} \Pr\left(\frac{M_n^{(i)} - b_n^{(i)}}{a_n^{(i)}} \leq y\right) = G_i(y), \tag{6}$$

which therefore is of the same type as Equation (5).

In practice, it is common to first transform the marginal distributions to a particular distribution before fitting a multivariate GEV distribution. In this paper, we choose the unit Fréchet transformation

$$z = -\frac{1}{\log G_i(y)}. \tag{7}$$

Multivariate Extreme Value Theory

According to Propositions 5.10 and 5.11 in Resnick (1987), the representation of a multivariate GEV distribution with unit Fréchet margins can be written as

$$G(\boldsymbol{y}) = \exp\{-V(\boldsymbol{z})\}, \tag{8}$$

where $V(\cdot)$, the exponent measure, has a functional representation

$$V(\boldsymbol{z}) = \int_{S_d} \max_{1\leq i\leq d} \left(\frac{q_i}{z_i}\right) d\phi(\boldsymbol{q}), \tag{9}$$

with ϕ being a finite spectral measure on $S_d = \{\boldsymbol{q} \in \mathbb{R}^d : \|\boldsymbol{q}\| = 1\}$, and $\|\cdot\|$ representing an arbitrary norm in $\mathbb{R}^d$. We also impose a constraint such that, for $1 \leq i \leq d$,

$$\int_{S_d} q_i d\phi(q_i) = 1, \tag{10}$$

but beyond this the spectral measure ϕ is unknown.

Multivariate Extreme Value Theory

As in this study we focus on assessing the upper tail dependence between temperature and mortality, we adopt the symmetric logistic model for the function V, which is a natural candidate and a commonly used dependence model in bivariate POT studies (see *e.g.* Tawn, 1990; Coles *et al.*, 1999; Rootzén and Tajvidi, 2006). Under the symmetric logistic model,

$$V(z_1, z_2) = (z_1^{-r} + z_2^{-r})^{1/r}, \qquad r \geq 1, \tag{11}$$

which can be retrieved from Equation (9) with a suitably chosen spectral measure ϕ on S_2. The exponent measure $V(z_1, z_2)$ determines the strength of dependence between the two margins. In particular, independence is obtained when $r = 1$, and perfect dependence is obtained as $r \to \infty$.

Multivariate Extreme Value Theory

The multivariate POT theorem then states that, for a random vector $\mathbf{X}$ distributed by $F \in \mathrm{MDA}(G)$, assuming $0 < G(0) < 1$ without loss of generality, the conditional distribution of $\boldsymbol{a}_n^{-1}(\boldsymbol{X} - \boldsymbol{b}_n)$ given $\boldsymbol{X} \nleq \boldsymbol{b}_n$ converges to the multivariate GPD as

$$H(\boldsymbol{y}) = \frac{1}{-\log G(0)} \log \frac{G(\boldsymbol{y})}{G(\boldsymbol{y} \wedge \boldsymbol{0})}, \tag{12}$$

which is defined for all $\boldsymbol{y} \in \mathbb{R}^d$ such that $G(\boldsymbol{y}) > 0$. In particular, $H(\boldsymbol{y}) = 0$ for $\boldsymbol{y} < 0$ and $H(\boldsymbol{y}) = 1 - \frac{\log G(\boldsymbol{y})}{\log G(0)}$ for $\boldsymbol{y} > 0$ (Rootzén and Tajvidi, 2006; Rootzén *et al.*, 2018a,b).

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Empirical Results

The Pickands dependence function $A : [0,1] \rightarrow [0,1]$ is defined as

$$A(\omega) = \int_{S_2} \max\left(\omega q_1, (1-\omega) q_2\right) d\phi(\boldsymbol{q}), \qquad 0 \leq \omega \leq 1, \tag{13}$$

which links the function V through the relation

$$A(\omega) = \frac{V(z_1, z_2)}{z_1^{-1} + z_2^{-1}}, \tag{14}$$

with $\omega = \frac{z_2}{z_1+z_2}$. By Equation (10), it is clear that $A(0) = A(1) = 1$. If two random variables with unit Fréchet margins are independent, then $A(\omega) = 1$ for all $0 \leq \omega \leq 1$, while if they are perfectly dependent, then $A(\omega) = \max(\omega, 1-\omega)$ for all $0 \leq \omega \leq 1$.

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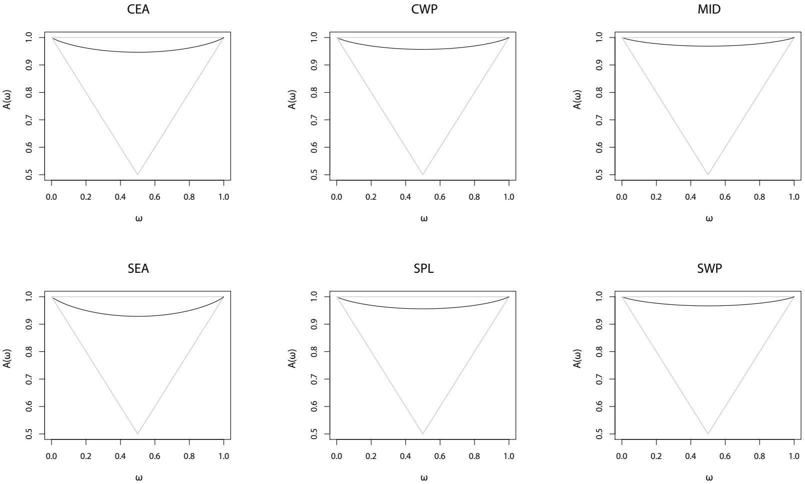
Empirical Results



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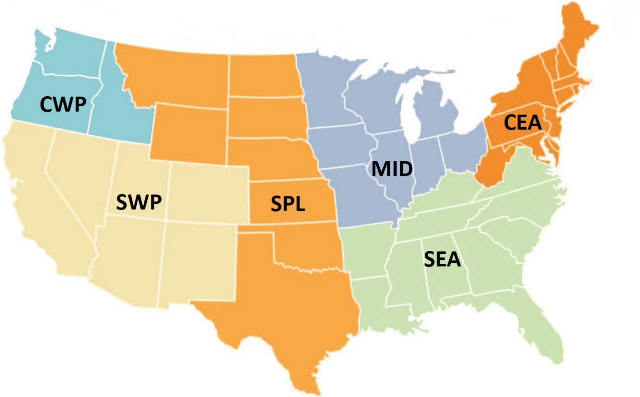
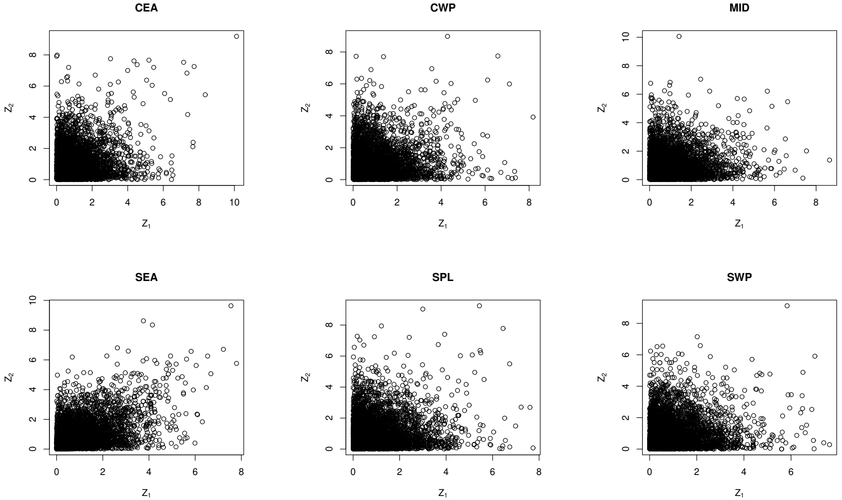


Source: Actuaries Climate Index Executive Summary (2018), Page 4, Figure 2

Empirical Results



Conclusions

Li, H., Tang, Q., 2022. Joint extremes in temperature and mortality: A bivariate POT approach. North American Actuarial Journal, 26(1), 43–63.

Frequency of extreme hot temperatures
➔ weak impact on death counts

Heatwaves?? A heatwave is generally defined in terms of a consecutive period of excessively hot weather (4 days)

“Harvesting effect” or “Mortality displacement”

A simple measure of monthly hot temperature frequency may not be adequate

Frequency of extreme cold weather
➔ stronger impact on older people aged 55–84 and 85+

Cold weather can cause substantial short-term increase in mortality

Epidemics of influenza are likely to be associated with extreme cold weather

The increase in mortality following extreme cold is long lasting

The elderly are more fragile to extreme temperatures

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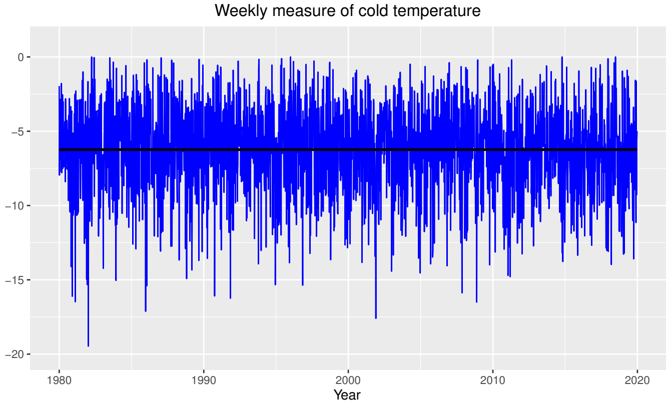

Figure 1: Weekly measures of extreme cold temperature

Data Description and Modeling

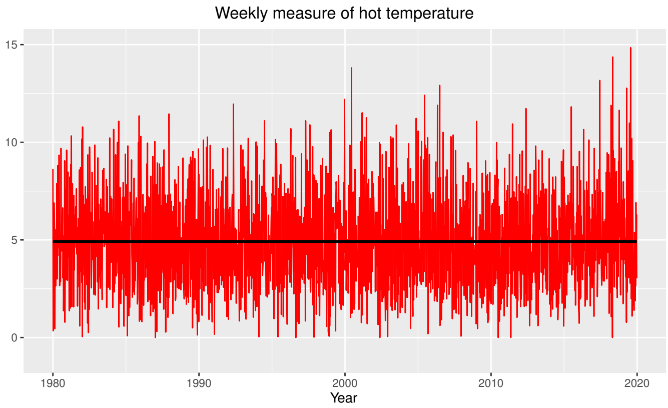

Figure 2: Weekly measures of extreme hot temperature

Data Description and Modeling

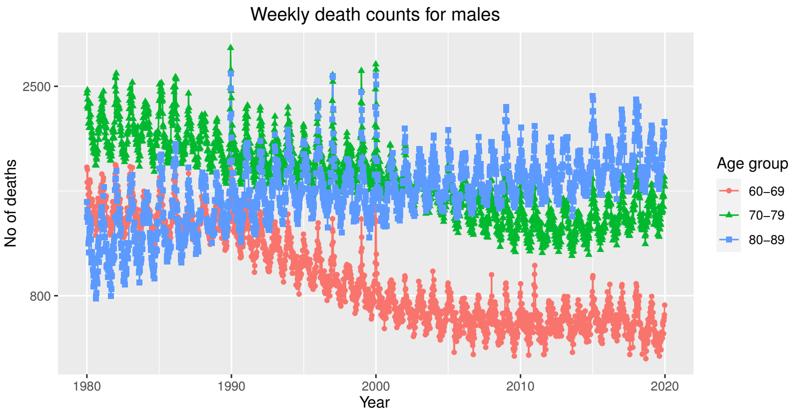

Figure 3: Weekly death counts for England & Wales: Males

Data Description and Modeling

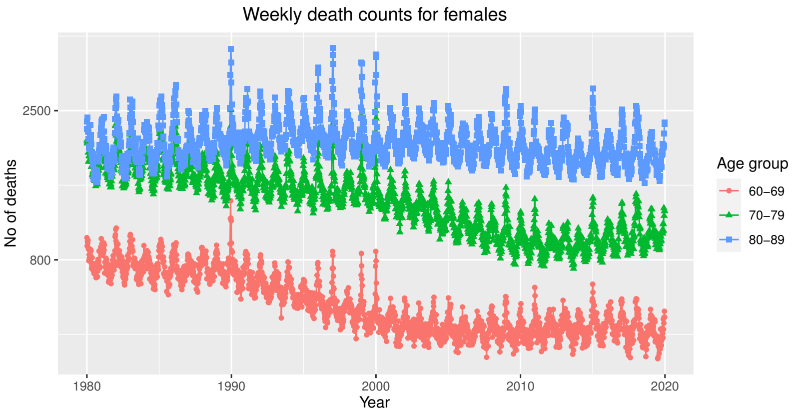

Figure 4: Weekly death counts for England & Wales: Females

Empirical Results

Coles *et al.* (1999) developed the index χ to measure extreme dependence for bivariate random variables. Assuming that random variables Z_1 and Z_2 have the same marginal distribution F, the index χ is defined as

$$\chi = \lim_{u \uparrow 1} \Pr\left(F(Z_2) > u \middle| F(Z_1) > u \right). \tag{15}$$

Thus, χ denotes the probability of one variable reaching the extreme value given that the other variable has already reached it. If $\chi = 0$, the two variables are said to be asymptotically independent. While for full tail dependence, we have $\chi = 1$.

Empirical Results

Table 1: Extreme dependence measure χ based on the bivariate POT analysis

Male												
Lag	0			1			2			3		
Age	60–69	70–79	80–89	60–69	70–79	80–89	60–69	70–79	80–89	60–69	70–79	80–89
Tmin	0.000	0.001	0.001	**0.087**	**0.091**	**0.132**	0.037	0.039	0.018	0.014	0.012	0.001
Tmax	**0.059**	**0.076**	**0.148**	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.001
Female												
Lag	0			1			2			3		
Age	60–69	70–79	80–89	60–69	70–79	80–89	60–69	70–79	80–89	60–69	70–79	80–89
Tmin	0.000	0.001	0.001	**0.055**	**0.092**	**0.129**	0.019	0.039	0.027	0.000	0.001	0.011
Tmax	**0.072**	**0.080**	**0.130**	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Empirical Results

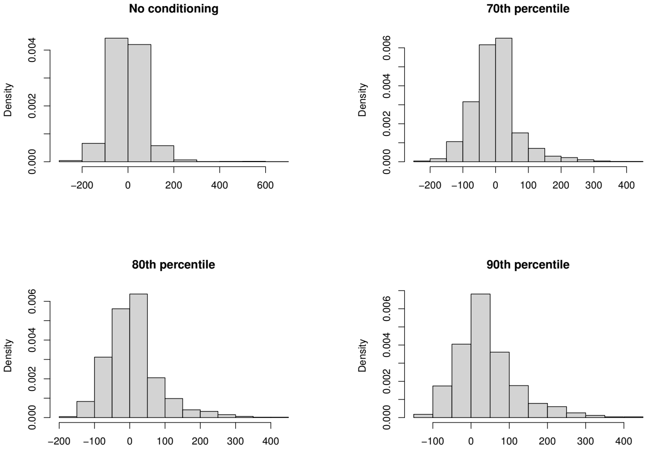

Figure 5: Density functions of excess deaths under different T_{cold} scenarios: Males, 80–89

Empirical Results

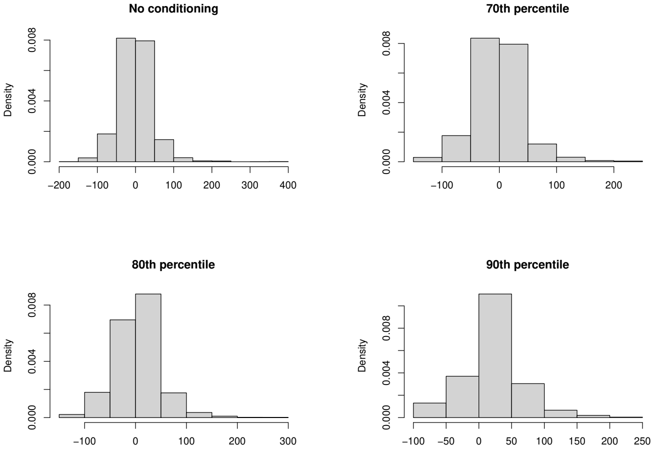

Figure 6: Density functions of excess deaths under different T_{cold} scenarios: Males, 60–69

What did we find?

A, Chaudhry., M, Leitschkis., Li, H., Tang, Q., 2023. An EVT Approach to Quantifying Mortality Risk of Extreme Temperatures.

Frequency of extreme hot temperatures
➔ impact on older people

Short-term increase in mortality happens immediately after extreme hot temperature events.

Consistent with the impact of heatwaves.

Frequency of extreme cold weather
➔ impact on older people

The increase in mortality following extreme cold is longer lasting

Short-term increase in mortality happens one week after extreme cold temperature events.

The "oldest old" are more fragile to extreme temperatures

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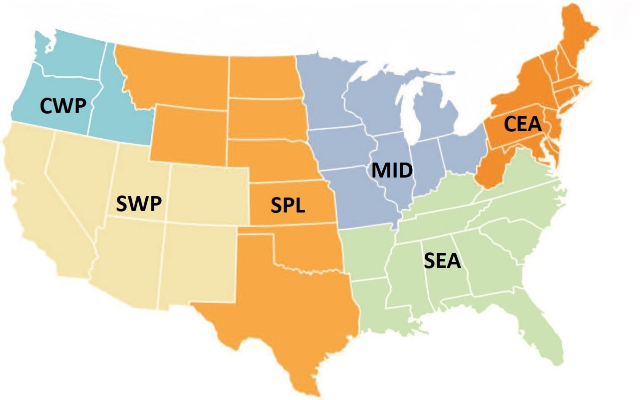
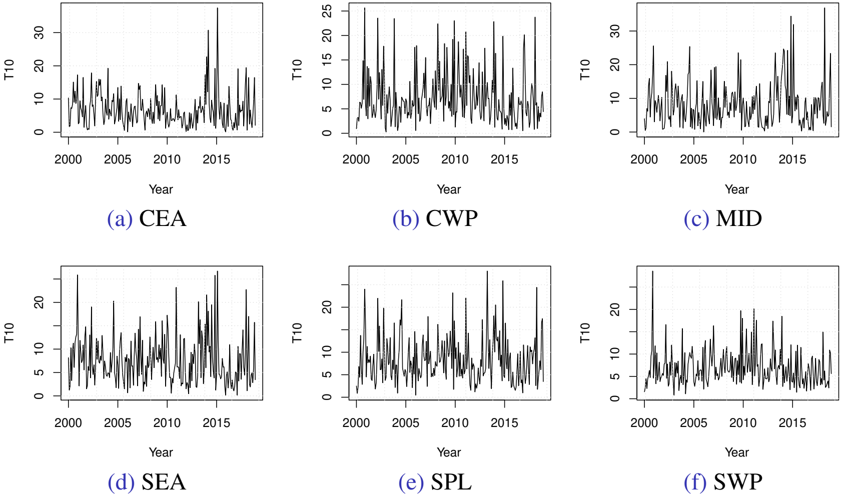


Source: Actuaries Climate Index Executive Summary (2018), Page 4, Figure 2

$T10$ index for extreme cold temperatures

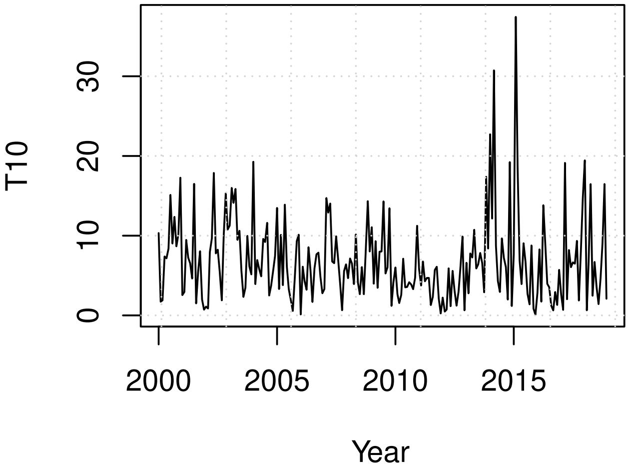


(a) CEA (b) CWP (c) MID

(d) SEA (e) SPL (f) SWP

Figure 7: $T10$ index over 2000–2018.

$T10$ index - Central East Atlantic (CEA)



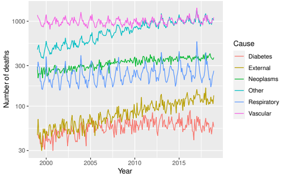
Cause-of-death definitions based on International Codification of Diseases

Table 2: Codification of five major causes of death

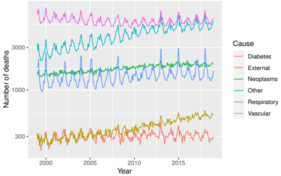
Cause of death	ICD-10 code
Diabetes	E10–E14
External	V01–Y89
Respiratory	J09–J98
Neoplasms	C00–D48
Vascular	I00–I78

Cause of death data

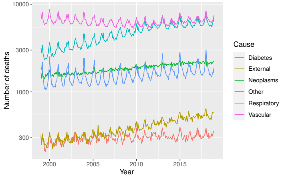
(a) CEA



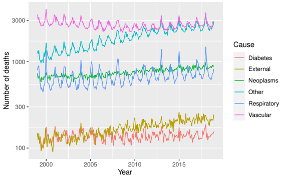
(b) CWP



(c) MID



(d) SEA

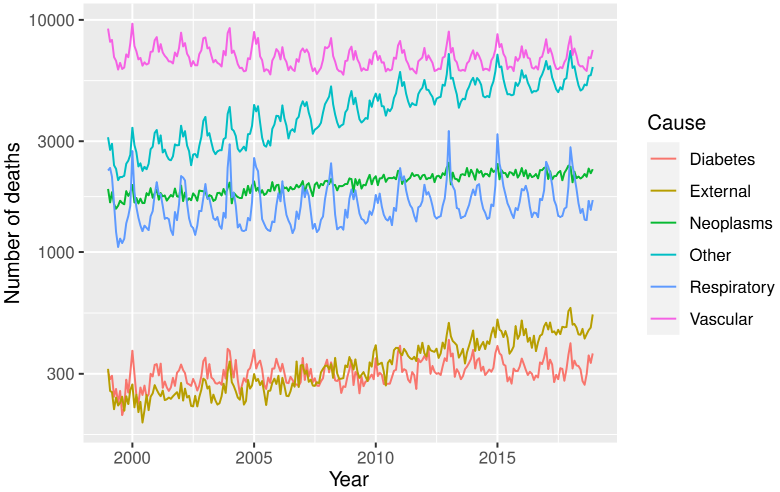


(e) SPL

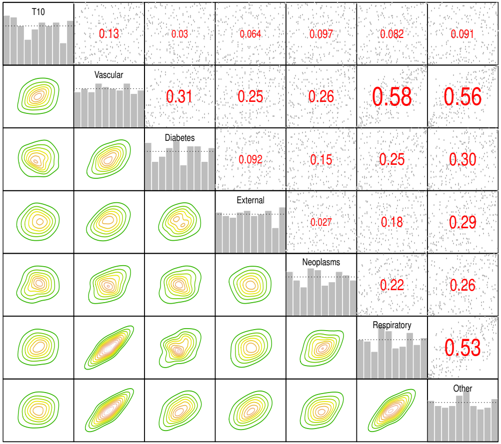
(f) SWP

Figure 8: Monthly death counts for ages 85+.

Cause of death data - Central East Atlantic (CEA)



Pairwise dependence structure



A quick introduction to Vine-copula modeling

Key idea: is to construct a flexible dependence structure across variables using pair-copulas as **bivariate building blocks** Aas *et al.* (2009).

Consider a simplified case with three causes of death, namely A, B, and C. Under the vine copula framework, the joint probability distribution f_{ABC} can be expressed as follows

$$f_{ABC} = C_{AC} \times C_{BC} \times C_{AB|C} \times f_A \times f_B \times f_C, \tag{16}$$

where C denotes bivariate pair-copulas and f denotes marginal distributions. As such, the joint density of excess deaths is broken down into a product of **bivariate copulas** and **marginal densities**.

A quick introduction to vine copula modeling

AC could be assigned a copula with **upper tail dependence** (*e.g.* Gumbel), BC could be assigned a copula with **lower tail dependence** (*e.g.* Clayton) and $AB|C$ could be assigned a copula with **no tail dependence** (*e.g.* Gaussian).

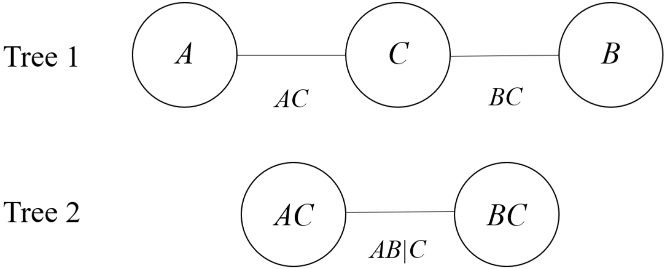


Figure 9: Example of an R-vine tree sequence

Three different climate scenarios

In particular, we analyze the distribution of excess deaths at time **t** under three temperature scenarios as follows

1. The $T10$ index at time t exceeds its 90th percentile.
2. The $T10$ index at time $t-1$ exceeds its 90th percentile.
3. The $T10$ index at both time t and $t-1$ exceeds its 90th percentile.

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Empirical results

Table 3: Excess deaths breakdown by causes: Scenario 1

Region	Diabetes	External	Neoplasms	Other	Respiratory	Vascular
CEA	1.3%	1.1%	3.9%	28.2%	25.3%	**40.2%**
CWP	1.3%	3.7%	-1.3%	**40.5%**	30.2%	25.6%
MID	0.6%	0.9%	-2.6%	14.8%	**61.8%**	24.4%
SEA	1.2%	2.8%	4.0%	40.1%	11.3%	**40.7%**
SPL	0.4%	5.7%	4.5%	**38.0%**	23.0%	28.3%
SWP	1.8%	1.0%	3.3%	**44.4%**	12.2%	37.3%

Empirical results

Table 4: Excess deaths breakdown by causes: Scenario 2

Region	Diabetes	External	Neoplasms	Other	Respiratory	Vascular
CEA	8.0%	-7.5%	-6.6%	45.5%	**47.3%**	13.2%
CWP	3.2%	3.3%	-1.0%	35.2%	**39.2%**	20.1%
MID	-0.6%	-0.3%	-1.9%	-4.2%	**117.4%**	-10.5%
SEA	0.3%	0.5%	-1.5%	37.4%	23.4%	**39.9%**
SPL	1.6%	2.7%	-1.8%	-30.9%	40.2%	**88.2%**
SWP	9.5%	0.4%	-26.4%	**102.0%**	43.3%	-28.8%

Empirical results

Table 5: Excess deaths breakdown by causes: Scenario 3

Region	Diabetes	External	Neoplasms	Other	Respiratory	Vascular
CEA	2.1%	-0.1%	2.0%	29.9%	32.0%	**34.0%**
CWP	1.9%	3.4%	-0.9%	35.5%	**36.2%**	24.0%
MID	0.1%	0.4%	-2.8%	8.3%	**81.0%**	12.9%
SEA	0.9%	1.9%	2.2%	37.7%	16.8%	**40.5%**
SPL	1.0%	4.5%	2.3%	15.7%	27.3%	**49.1%**
SWP	1.2%	0.2%	0.7%	**65.5%**	13.5%	19.0%

Empirical results

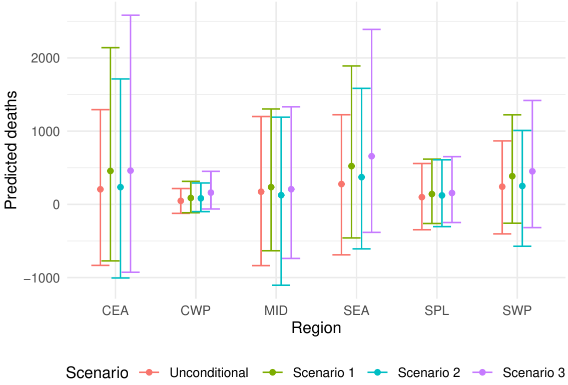
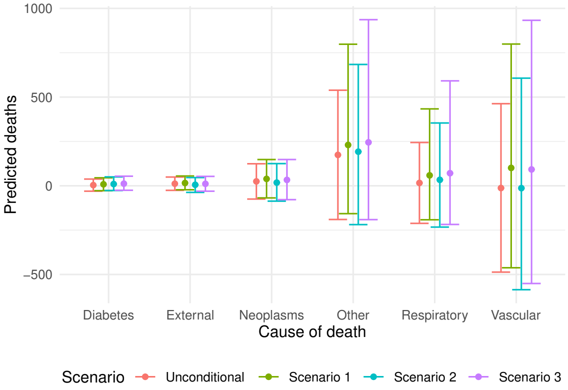
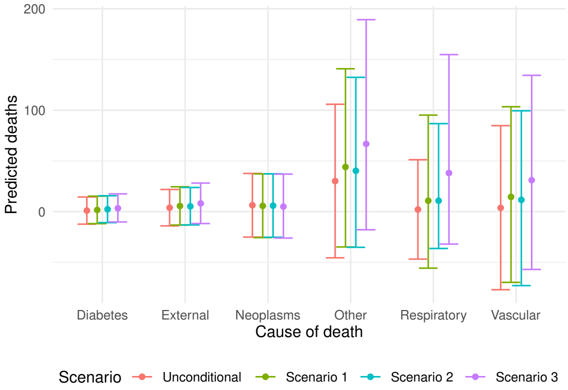


Figure 10: Prediction intervals of monthly total deaths at 10th, 50th, and 90th percentiles.

Empirical results



(a) CEA



(b) CWP

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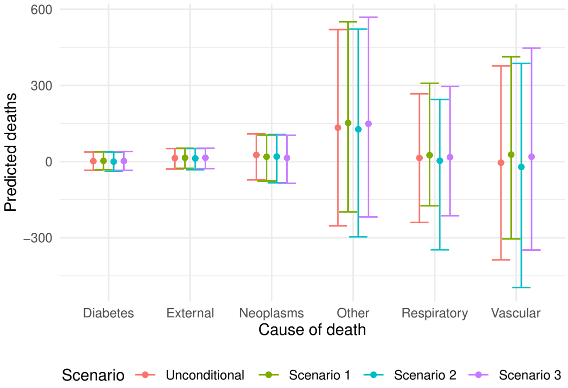
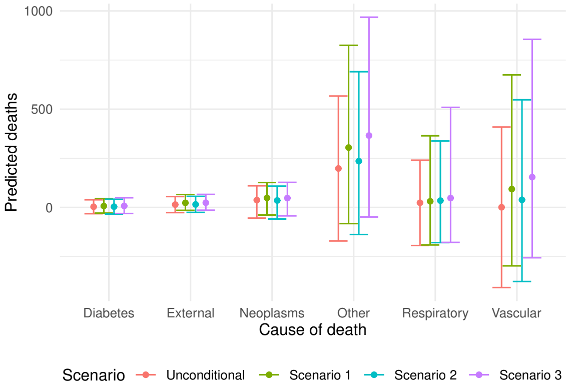
Empirical Results

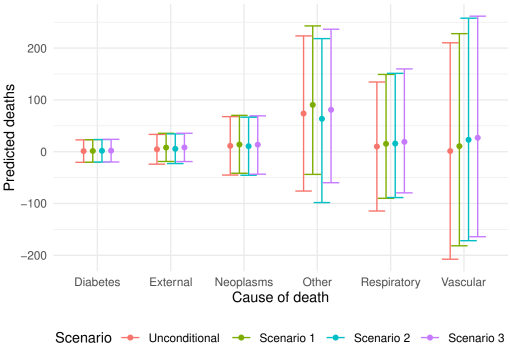


(c) MID

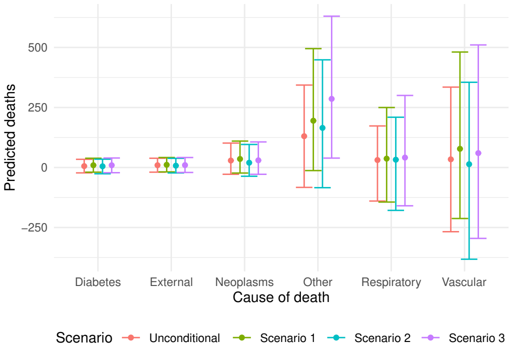


(d) SEA

Empirical Results



(e) SPL



(f) SWP

Figure 11: Prediction intervals of monthly cause-specific deaths at 10th, 50th, and 90th percentiles.

Empirical results

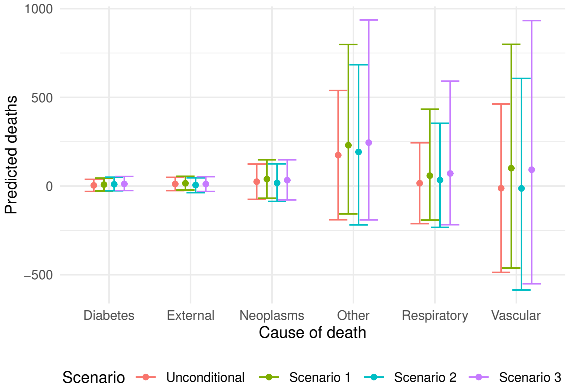


Figure 12: Prediction intervals of monthly total deaths at 10th, 50th, and 90th percentiles for CEA.

Outline

1 Background information

2 Joint extremes in temperature and mortality

3 Excess mortality under climate scenarios

4 Cold-related cause-of-death mortality

5 The ultimate research questions

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The ultimate research questions

Our result is expected to provide insights into the following questions:

1. Who are the excess deaths? – Find the age groups that are particularly sensitive to climate change.
2. When do excess deaths occur? – Determine if more excess deaths occur in winter or summer.
3. Where are the excess deaths? – Identify regions that are most vulnerable to climate change.

Questions and discussions

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